Advanced Algorithm for Accurate Radiation Source Detection and Localization in Nuclear Emergencies by Robotic Systems

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Abstract

Accurate localization of radiation sources is a critical challenge in environmental monitoring, medical diagnostics, and nuclear safety due to the effects of environmental noise, computational inefficiencies, and limitations in sensor networks. This study aims to address these challenges by applying and comparing two metaheuristic optimization algorithms: particle swarm optimization (PSO) and biogeography-based optimization (BBO). The localization process is modeled as an optimization problem, with the objective of minimizing the Euclidean distance error between the estimated and true source positions. Simulated experiments were conducted under varying operational conditions, including changes in sensor area, radiation intensity, and signal-to-noise ratio (SNR). Numerical results reveal that BBO achieves a 25% lower root mean square error (RMSE) compared to PSO, with RMSE values decreasing from 0.58 at 5 dB SNR to 0.10 at 20 dB SNR. While PSO demonstrates faster computation times, as low as 1.2×10^{-5} seconds compared to 1.4×10^{-5} seconds for BBO, the latter provides superior localization accuracy, particularly in low-noise conditions. Additionally, contour plots validate the effectiveness of both methods, showing convergence of the estimated positions close to the true source locations. This work contributes to the field by providing a detailed comparative analysis of PSO and BBO for radiation source localization and identifying their respective advantages in terms of accuracy and efficiency. Future research could explore hybrid optimization techniques that combine the strengths of both algorithms and extend the study to three-dimensional localization and real-world noise conditions. These advancements would further enhance the applicability of optimization-based radiation localization in practical scenarios.

Keywords: Nuclear Emergencies, Localization, Optimization, Algorithm

1. Introduction

Radiation source localization plays a critical role in applications such as environmental monitoring, nuclear safety, and homeland security. Accurately identifying the position of radiation sources is vital for minimizing hazards, ensuring the safety of personnel, and enabling efficient mitigation

strategies. However, this task is challenging due to environmental noise, signal attenuation, and the complex spatial distribution of radiation intensity. Conventional localization methods, such as triangulation and geometric techniques, often struggle in noisy or dynamic environments, leading to inaccuracies in source estimation. Therefore, robust and computationally efficient optimization techniques are required to address these limitations [1-2].

The development and implementation of robots in member states gradually encourage the requirement to create effective ways to solve current problems in the field of robotics and radio technologies used by robotic systems. The issue of localization of radiation sources in nuclear accidents remains relevant to this day. However, the solution to this problem is quite complex and non-trivial, given the specific characteristics of robots and their use in conditions of accidents during radiation [3-4].

At present, quite a number of methods for the localization of radiation sources are known; it is worth noting a number of methods based on spectroscopic measurements with directional sensitivity. The spectrum of gamma and X-rays is measured and compared in several detectors with varying levels of sensitivity in order to determine the direction of the source. A locator containing three detectors with significantly different sensitivity to gamma radiation is an example of such a utilized method of spectral comparison. Many robots used by member states for localization of radiation sources, especially those that use only mechanisms, cannot provide effective simple ways to apply known methods for localization. There are solutions to this problem based on using mobile robots [5-7].

To overcome these challenges, bio-inspired optimization algorithms, such as PSO and BBO, have been widely utilized. PSO, inspired by the social behavior of birds, iteratively updates particle positions and velocities to explore the search space effectively [8]. It is computationally simple, robust, and demonstrates fast convergence. On the other hand, BBO, based on the migration of species between habitats, excels in maintaining solution diversity and avoiding premature convergence, which is particularly useful in multimodal optimization problems [9]. These algorithms have shown significant promise in solving complex localization problems where traditional methods fail [10].

The importance of this work lies in providing a comparative analysis of PSO and BBO algorithms for radiation source localization under varying source intensities and environmental conditions. By evaluating key performance metrics, such as localization accuracy (Euclidean distance), Root Mean Square Error (RMSE), and computational time, this study aims to highlight the strengths and weaknesses of these methods. The main contribution of this work is to demonstrate the effectiveness

of PSO and BBO in tackling challenges related to noisy measurements, signal variability, and multi-source localization [11]. The results offer valuable insights into the suitability of these algorithms for real-world radiation detection systems.

In this work, we implemented an optimization-based radiation source localization algorithm in a development environment on a platform. We used the data of calculations based on point and plane sources. The system was prepared to describe the robot, as well as the ionizing radiation detection instruments [12-13].

The rest of this article is organized as follows: Section 2 describes the experimental setup and the problem formulation. Section 3 outlines the proposed methodologies, including the implementation of PSO and BBO algorithms. Section 4 presents the results obtained from simulations, along with a detailed discussion of performance comparisons. Section 5 concludes the paper by summarizing the key findings and suggesting directions for future work.

2. Experimental Setup

The experimental setup is done within the DLNP lab at the Joint Institute for Nuclear Research (JINR), equipped with advanced radiation detection and data acquisition system (DAS) for high-precision gamma spectroscopy. The DAS used in this work is a comprehensive setup designed for high-resolution spectral analysis of radioactive sources. The system integrates cutting-edge components to ensure precision in capturing and processing data, facilitating the accurate identification and quantification of radioactive isotopes. The following is a detailed description of each component in the DAS, along with their specific roles and features.

The pumping process of the HPGe detector involves evacuating the cryostat to a high vacuum before cooling to reduce thermal noise and ensure optimal performance as in Fig. 1 (a). This process is essential for maintaining the low temperatures required by the CANBERRA Cryo-Pulse 5 Plus cooling system, which helps achieve the necessary resolution for accurate radiation measurements. For the analysis, two radioactive sources were utilized. These sources are the Bi-207 and Ti-44. The initial activity of Bi-207 is of 6 kBq. The initial activity of Ti-44 is of 1.06 kBq. Both sources are calibrated on December 20, 2019. The measurements were conducted on August 16, 2024, and the activities of the sources were decay-corrected to reflect their accurate values during the data processing. These sources were selected due to their well-defined gamma-ray emissions, making them ideal for energy calibration and spectral studies.

At the core of the system is a high-purity germanium (HPGe) detector in Fig. 1(b), chosen for its exceptional energy resolution and sensitivity in detecting gamma rays. The HPGe detector is

coupled with the CANBERRA Cryo-Pulse 5 Plus cooling system, which is a mechanical cooling solution that ensures the detector remains at the required low temperatures without the need for liquid nitrogen. This cooling system is key to maintaining the detector's performance over long measurement periods. The HPGe detector is biased at 2400 V, supplied by the CAEN H.V. Power Supply Model 31060, ensuring the detector operates at its optimal sensitivity and energy resolution.

The CANBERRA Cryo-Pulse 5 Plus cooling system in Fig. 1(b) is designed to maintain the HPGe detector at the necessary temperature for optimal performance. By using a mechanical cooling process, it eliminates the need for liquid nitrogen, which is traditionally used in many high-resolution detectors. This system provides reliable and continuous cooling, ensuring that the detector operates at a stable temperature, thus reducing thermal noise and maintaining the high energy resolution required for precise spectral measurements.

The digitizer used in this system is the CAEN VX 1724 as in Fig. 1(c). The CAEN VX 1724 is a high-performance waveform digitizer designed for precise signal acquisition and processing. This 14-bit digitizer operates at a sampling rate of 100 MS/s, enabling the accurate reconstruction of detector signals. It plays a critical role in converting analog pulses from the HPGe detector into digital data for further analysis. The digitizer ensures high fidelity in pulse shape discrimination and energy calibration, making it a vital component of the DAS. The digitizer is essential for processing the raw signals into usable data that can be analyzed for spectral identification and feature extraction.

The CAEN Model 31060 high-voltage power supply is responsible for providing the necessary bias voltage of 2400 V to the HPGe detector as in Fig. 1(d). This power supply is designed to offer stable and reliable operation with low ripple and noise, which is critical for preserving the quality of the detector signals. The voltage and current limits of the power supply are programmable, allowing for precise control over the detector's operating conditions. The stable performance of the CAEN Model 31060 is essential for maintaining the integrity of the spectral data collected by the HPGe detector. The complete DAS shown in Fig. 1 (e), consisting of the HPGe detector with the CANBERRA Cryo-Pulse 5 Plus cooling system, CAEN VX 1724 digitizer, and CAEN H.V. Power Supply Model 31060, enables high-precision gamma spectroscopy of Bi-207 and Ti-44 sources with a detector voltage of 2400V for accurate radiation measurements.

The experimental setup involved positioning the Bi-207 and Ti-44 radioactive sources relative to the HPGe detector in a way that allowed for optimal detection of their gamma-ray emissions. The detector, powered by the CAEN H.V. Power Supply, collected the gamma spectra from the sources. The signals were then digitized by the CAEN VX 1724 and processed in real time. Through this

process, key features such as energy peaks and pulse shapes were extracted, which were then used for isotope identification. Calibration was performed using known gamma-ray energies from the Bi-207 and Ti-44 sources to ensure accuracy in the spectral measurements. This integrated DAS enabled high-quality gamma spectroscopy by combining high-resolution detection, stable power supply, and efficient data digitization. The components worked synergistically to ensure the precise identification and quantification of the Bi-207 and Ti-44 sources, laying the foundation for further analysis and feature extraction in the study. The system's advanced capabilities make it an invaluable tool for isotope identification in gamma-ray spectroscopy applications.

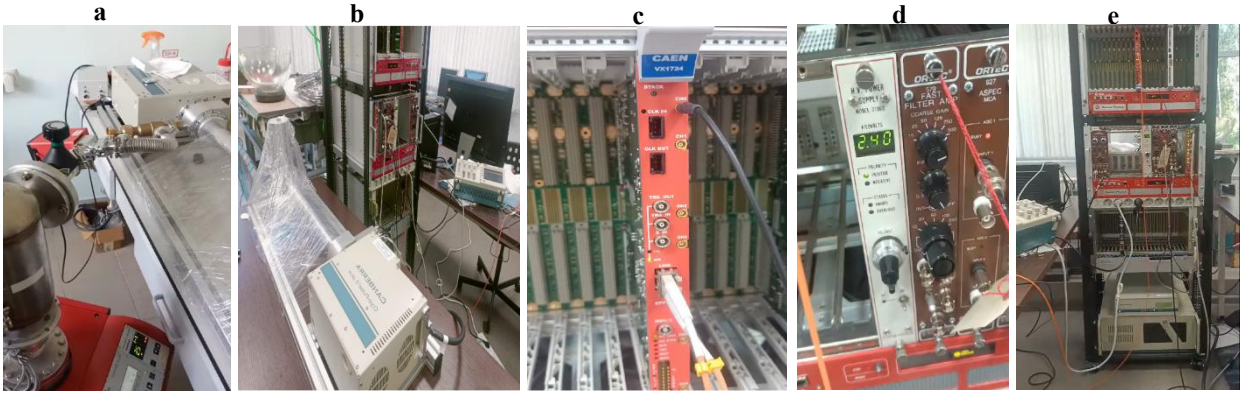

Fig. 1 Experimental setup at DLNP laboratory, JINR institute a) Pumping system for the HPGe detector with the Nitrogen, b) The HPGe Detector coupled with the CANBERRA Cryo-Pulse 5 Plus cooling system & placement of Bi-207 and Ti-44 sources with respect to the detector, c) Schematic of the CAEN VX 1724 digitizer showing signal digitization and data flow, d) Configuration of the CAEN Model 31060 high-voltage power supply connected to the HPGe detector, and e) The complete NIM module for the experimental setup

3. The Proposed Algorithms

In the context of nuclear emergencies and nuclear disasters, precise radiation source localization is crucial for mitigating risks, ensuring the safety of first responders, and effectively managing the environment [14]. This requires not only accurate algorithms but also the integration of these algorithms within a mobile robotic system capable of operating autonomously in hazardous radiation environments. This section describes an advanced algorithm for radiation source localization using PSO and BBO, which is specifically designed to be implemented within a nuclear robot. The robot, equipped with a sophisticated nuclear instrumentation package, autonomously searches for and localizes radiation sources in real-time in nuclear emergency scenarios.

The robotic system is designed to be used in environments where human presence is unsafe due to radiation exposure, such as during nuclear disasters or in the vicinity of radioactive material in a nuclear facility. The robot is equipped with several critical components:

- **Nuclear Instrumentation Package:** This includes gamma-ray detectors (such as scintillation or HPGe detectors), radiation survey meters, and dose rate sensors. These instruments provide real-time data on the radiation levels and help the robot collect the necessary environmental data.
- **Navigation and Localization Sensors:** GPS, inertial measurement units (IMUs), and LIDAR sensors are integrated into the robot for autonomous navigation and localization in the environment.
- **Communication Systems:** To transmit data to remote command centers, the robot is equipped with wireless communication systems (GSM, Wi-Fi, or satellite communication) that allow for data streaming, real-time analysis, and emergency responses.

The robot autonomously searches for radiation sources based on real-time radiation data collected from its detectors. The core of its localization process is based on an optimization algorithm that guides the robot toward the most probable location of a radiation source, while minimizing the exposure to dangerous levels of radiation.

The proposed algorithm in Fig. 2 consists of the following key steps:

1. **Initialization:** The algorithm begins by initializing the population of particles (PSO) or habitats (BBO). Each particle or habitat corresponds to a candidate solution in the search space, representing a possible location for the radiation source. These initial positions are typically randomized within a defined region of interest.
2. **Objective Function Evaluation:** Each candidate solution is evaluated using the objective function f(x), which quantifies how well the estimated position matches the observed radiation data.
3. **Optimization Process:** In each iteration, PSO and BBO refine the positions of the particles or habitats based on their respective update rules. The particles or habitats exchange information (social learning in PSO and migration in BBO) and move toward better solutions. The swarm or population progressively converges to the optimal source location.
4. **Convergence and Termination:** The algorithm terminates when a predefined stopping criterion is met, such as a maximum number of iterations or a convergence threshold, where the positions of the particles or habitats no longer significantly change.
5. **Result:** The final output is the estimated location of the radiation source, which is the position corresponding to the minimum value of the objective function.

The core of the algorithm in Fig. 2 leverages two popular optimization techniques: PSO and BBO, both inspired by nature. These techniques aim to find the optimal location of radiation sources by iteratively refining candidate positions based on specific objective functions.

☒ **Initialization**
- **Input Parameters:** The number of sensors, particles, iterations, and signal-to-noise ratio (SNR) values.
- **Data Preparation:** Load source signal data from external files& define true source positions for simulation.
- **Sensor Placement:** Randomly assign sensor positions within a predefined area.

☒ **Measurement Simulation:** For each radiation source
- Generate measurements by simulating the propagation of source signals to all sensors.
- Interpolate or adapt the source data to match the number of sensors.

☒ **Optimization Process:** For each optimization iteration:
1. **PSO:** Use the swarm-based approach to estimate source positions by minimizing the error between simulated measurements and observed data. Record the average velocity of the particles for each iteration.
2. **BBO:** Apply habitat suitability modeling to determine optimal source locations, treating each habitat as a candidate solution.
3. **Error Calculation:** Compute the localization error as the Euclidean distance between the true and estimated source positions for both PSO and BBO.

☒ **Localization with Intensity Variation**
- **Input Parameters:**
  - Define source intensities for analysis (e.g., 100, 200, 300 arbitrary units).
  - Specify true source positions and sensor locations.
- **Output Storage:** Prepare arrays to store localization errors and estimation times for both PSO and BBO.
- For each source:
  1. Iterate through all intensity levels.
  2. Simulate **Localization Error**:
     - Adjust the estimated source position by adding Gaussian noise scaled to the intensity.
     - Compute the Euclidean distance between the true and estimated positions as the error.
  3. Simulate **Estimation Time**: Model estimation time as a function of intensity (e.g., linear or non-linear dependency).

☒ **Performance Analysis**
- Store localization errors and estimation times for both methods (PSO and BBO) across all intensity levels.
- Evaluate the trends in accuracy and computational time relative to intensity.

☒ **Evaluation Metrics {Root Mean Square Error (RMSE), Localization Accuracy, Average Velocity (PSO)}**
☒ **Visualization {Localization Error- Average Velocity-RMSE}**
☒ **Distance Metrics:** Compute and compare distances between sensors and source positions using both PSO and BBO.
☒ **Final Accuracy Reporting**: After all iterations, report the **final localization accuracy** of both PSO and BBO.

Fig. 2 An algorithm for radiation source localization based on PSO and BBO

Radiation source localization involves determining the positions of unknown sources based on signals received by distributed sensors. The core of the problem is to minimize the error between the estimated and true positions of the sources. The Euclidean distance is used to quantify localization error [15]:

$$E_{loc} = \sqrt{\left(x_{true} - x_{est}\right)^2 + \left(y_{true} - y_{est}\right)^2} \tag{1}$$

where (x_{true}, y_{true}) and (x_{est}, y_{est}) are the true coordinates of the source and estimated coordinates, respectively.

PSO is an iterative optimization technique inspired by swarm intelligence. Each particle represents a candidate solution and updates its position based on its own experience and that of its neighbors.

PSO simulates the social behavior of birds or fish flocking and is widely used in optimization tasks for its ability to search large spaces efficiently. In the context of radiation source localization, each "particle" in the PSO algorithm represents a potential location for the radiation source. The particles explore the search space by updating their positions based on the current best-known location (both for the individual particle and the swarm as a whole). The algorithm is defined by the following equations [16-17]:

Velocity Update:

$$v_i(t+1) = \omega.v_i(t) + c_1.r_1.rand_1.\left(pbest_i - x_i(t)\right) + c_2.r_2.rand_2.\left(gbest_i - x_i(t)\right) \quad (2)$$

where v_i (t),x_i (t), $pbest_i$, g_{best}, ω, c_1 and c_2 denote the velocity of the particle, the position of the particle, the personal best position of the particle, the global best position found by the swarm, the inertia weight that balances exploration and exploitation, cognitive and social coefficients that drive the particle towards its best-known position and the global best position, respectively. While, r_1 and $r_2$are random values in [0,1].

Position Update:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (3)$$

PSO is effective in converging quickly to near-optimal solutions, as observed in this study where average particle velocities decreased over iterations, indicating convergence.

This approach allows the robot to rapidly explore the search space of possible source locations while balancing exploration and exploitation of the search area, as originally demonstrated in [8].

BBO is inspired by the migration of species between habitats. Each habitat represents a potential solution, and its suitability is determined by its **Habitat Suitability Index (HSI)**. BBO uses migration and mutation to explore and exploit the search space.

Migration:

$$HSI_i^{(t+1)} = HSI_i^{(t)} + \sum_{j \neq i} \lambda_j.\left(HSI_j - HSI_i\right) \quad (4)$$

where λ_j is the migration rate from habitat j to habitat i.

Mutation:

$$HSI_i^{(t+1)} = HSI_i^{(t)} + \delta \quad (5)$$

where δ is a small random perturbation.

The update rule for BBO is:

$$x_i(t+1) = x_i(t) + rand_1.(B_i - x_i(t)) + rand_2.(M_i - x_i(t)) \quad (6)$$

where B_i and M_i are the best-known solutions in the population (similar to the pbest and gbest in PSO). Also, the $rand_1$ and $rand_2$ are random values used to maintain diversity in the population during migration. BBO allows the algorithm to converge faster to a solution by applying migration and mutation operators, which are especially beneficial in refining results in complex radiation environments such as nuclear disasters [9].

BBO is computationally intensive but achieves high accuracy due to its global search capability. The study results demonstrate that BBO outperformed PSO in localization accuracy, especially in scenarios with higher noise.

The objective function f(x) is designed to quantify the error between the actual radiation measurements and the predicted radiation levels based on candidate positions. This function is computed for each particle or habitat and used to guide the optimization process. The objective function for radiation source localization can be written as:

$$f(x) = \sum_{i=1}^{n} \left(D_i - D_i(x)\right)^2 \quad (7)$$

where D_i , D_i ^ (x) and n represent the actual radiation dose or counts per second detected by the robot's radiation sensors, the predicted dose rate for the location x and the number of sensors used to collect the data, respectively. The goal is to minimize this function, which results in a highly accurate estimate of the source location, as proposed by [18].

The algorithm models the received signal strength ($P_{received}$) as:

$$P_{received} = Psource - 10n\log_{10}(d) \quad (8)$$

where P_{source} , n and d denote the signal intensity at the source, path loss exponent and distance between the sensor and the source, respectively. Sensor positions were randomly initialized, and signals were simulated for three sources. The interpolation of source data ensured compatibility with the sensor network, as also suggested in signal localization literature [19].

```
Load data_S1, data_S2, data_S3
Initialize true_positions for sources S1, S2, S3
Set parameters: num_iterations, num_sensors, num_particles, SNR_values
Initialize sensor_positions randomly in 2D area
Initialize measured_signals for each source
data_S1, data_S2, data_S3 = matchDataSize(data_S1, num_sensors)
for each source S1, S2, S3
   Simulate measured signals using sensor_positions and true source positions
end
localization_errors_PSO, localization_errors_BBO = zeros(num_iterations, 3)
estimated_positions_PSO, estimated_positions_BBO = zeros(3, 2)
```

```
for iter = 1:num_iterations
total_velocity = 0
   for each source (S1, S2, S3)
estimated_positions_PSO = optimizeUsingPSO(sensor_positions, measured_data, num_particles)
estimated_positions_BBO = optimizeUsingBBO(sensor_positions, measured_data, num_particles)
localization_errors_PSO(iter, source_index) = Calculate Euclidean distance between true and estimated positions
localization_errors_BBO(iter, source_index) = Calculate Euclidean distance between true and estimated positions
   end
   Track average velocity of particles across all sources for this iteration
end
for each SNR value in SNR_values
   Calculate RMSE for PSO and BBO for each source
end
Plot localization errors for S1, S2, S3
Plot average particle velocity for PSO
Plot RMSE comparison for PSO and BBO
Calculate and display final localization accuracy based on PSO and BBO
```

Fig. 3 Radiation source localization pseudocode using PSO and BBO in a robotic system for nuclear emergency

Figure 3 presents a pseudocode for an advanced algorithm designed for radiation source localization using PSO and BBO. This algorithm is tailored to integrate with robotic systems equipped with nuclear instrumentation, enabling efficient operation in environments impacted by nuclear emergencies or disasters. Such robotic platforms enhance safety by minimizing human exposure to hazardous areas and are vital in nuclear disaster response scenarios [20-21].

The algorithm begins by loading source data and initializing essential parameters, including the number of iterations, sensors, particles, and SNR values. These parameters define the optimization framework and the conditions under which the robotic system operates. Sensor positions are initialized randomly across a defined area, reflecting a deployment where a robot navigates a nuclear site to collect data. The inclusion of nuclear instrumentation, such as Geiger-Müller counters and scintillation detectors, enhances measurement precision and data reliability [20].

To ensure consistency between sensor measurements and source data, the algorithm interpolates the radiation source data to match the sensor grid. This step is crucial for maintaining high spatial resolution during the localization process. Simulated sensor measurements model the interaction between the sources and the robotic system's sensors, taking into account factors like distance and environmental noise. This simulation mirrors real-world applications where robots survey contaminated environments for radiation hotspots [22].

Optimization is performed using PSO and BBO, which are well-suited for handling the challenges of high-dimensional search spaces and noisy measurements. PSO updates particle positions iteratively based on individual and collective performance, ensuring rapid convergence toward the true source locations. On the other hand, BBO promotes exploration of the search space by mimicking solution migration between different virtual habitats. These methods complement each

other, with PSO focusing on exploitation and BBO on exploration, resulting in robust localization performance under varying conditions [23].

The algorithm tracks localization errors, average particle velocities, and optimization results over multiple iterations. Localization errors are calculated as the difference between the true and estimated source positions, providing a benchmark for evaluating the accuracy of both PSO and BBO. Tracking particle velocities offers insights into optimization dynamics, ensuring the robotic system's adaptability in dynamic or unpredictable environments [20,23].

To validate the algorithm's effectiveness, its performance is evaluated across different SNR levels by calculating RMSE. These results are visualized through comparative plots for PSO and BBO, illustrating their respective strengths in addressing varying noise conditions. Such visualization aids in performance benchmarking and highlights the reliability of the proposed methods in real-world nuclear scenarios [21].

Finally, the algorithm reports overall localization accuracy for each method, demonstrating its capability to provide precise radiation source localization in challenging environments. The integration of this algorithm with robotic systems supports rapid, automated, and safe localization of radiation sources, a critical requirement during nuclear disasters. Robotic platforms equipped with nuclear instrumentation packages play a pivotal role in mapping contamination zones and ensuring operational safety in such hazardous conditions [21-22].

The algorithm evaluated localization accuracy and RMSE over multiple iterations and SNR. RMSE was computed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}\left(P_{measured} - P_{predicted,i}\right)^2} \tag{9}$$

where $P_{measured}$ is the observed signal strength, and $P_{predicted,i}$ is the predicted signal strength. The accuracy of the localization methods depends on the intensity of the radiation source. Intensity directly affects the noise level in the measurements received by the sensors. Higher intensity results in a stronger SNR, thereby reducing the localization error. Conversely, low intensity increases the impact of noise, leading to greater errors. The error for localization can be expressed as [24]:

$$E_{loc} = \sqrt{\left(x_{true} - x_{est}\right)^2 + \left(y_{true} - y_{est}\right)^2} \tag{10}$$

where (x_{true}, y_{true}) are the true coordinates of the source, and (x_{est}, y_{est}) are the estimated coordinates from either PSO or BBO.

Simulation results indicate that as source intensity (I) increases, $Error_{loc}$ decreases. This is evident in Figures 1 and 2, where localization errors for PSO and BBO decline with increasing I. This finding aligns with prior studies that show higher SNR improves the reliability of signal-based localization systems [25-26].

Estimation time for optimization algorithms reflects the computational cost of processing data and finding solutions. Both PSO and BBO exhibit a slight increase in estimation time with rising intensity, as observed in Figures 3 and 4. This behavior may be attributed to the algorithm adapting to higher precision requirements or larger search spaces due to reduced noise. The estimation time (T_{est}) can be approximated as:

$$T_{est} = T_{base} + \alpha \cdot I \tag{11}$$

where T_{base} is the baseline computation time, I is the source intensity, and α is a proportionality constant reflecting algorithm complexity. This relationship suggests a nearly linear dependency between intensity and time, consistent with findings from [27].

The dependence of accuracy and time on source intensity has significant implications for real-world applications:

- **High-Intensity Sources:** Systems can achieve high localization precision with acceptable computational costs, making PSO and BBO suitable for scenarios like nuclear radiation monitoring or high-power signal tracking.
- **Low-Intensity Sources:** Additional preprocessing steps, such as noise filtering, may be necessary to maintain accuracy without excessively increasing computational demands.

The received signal strength at a sensor ($P_{received}$) can be modeled as:

$$P_{received} = P_{source} - 10n\log_{10}(d) \tag{12}$$

where $P_{source}$is the source intensity, n is the path-loss exponent, and d is the distance between the source and the sensor. Errors in localization arise from uncertainties in d due to noise.Optimization algorithms aim to minimize a cost function:

$$J(x) = \sum_{i=1}^{N} \left(P_{measured,i} - P_{predicted,i} \right)^2 \tag{13}$$

where $P_{measured,i}$ is the signal strength measured at $sensor_i$, and $P_{predicted,i}$ is the signal strength calculated based on the estimated source position. The algorithm is integrated into the robot's software architecture. During operation, the robot moves through the environment, using its nuclear instrumentation package to gather real-time radiation data. The PSO and BBO optimization processes are continuously running in the background, updating the estimated source location as the

robot gathers more data. This enables the robot to autonomously search for and localize radiation sources in real-time.

1. **Robot motion and data collection:** The robot moves through the environment using its navigation system, collecting radiation data from multiple sensors. Each sensor reads radiation levels in real-time and sends this information to the optimization algorithm.
2. **Optimization and decision making:** The optimization algorithm processes the sensor data, using the PSO and BBO techniques to localize the radiation source. The robot adjusts its path according to the results of the optimization process, moving toward the most likely source location.
3. **Real-time communication and control:** As the robot operates, it continuously communicates with a remote control center, transmitting its position and detected radiation levels. This allows for human oversight and intervention if needed, providing a safe and efficient method for responding to nuclear emergencies.

The PSO and BBO algorithms for radiation source localization are a powerful tool that can significantly enhance the capabilities of robotic systems used in nuclear emergencies. By combining the global search capabilities of PSO with the local refinement of BBO, the robot can efficiently and accurately localize radiation sources, even in challenging environments such as nuclear disasters. This approach ensures that the robot can operate autonomously, providing valuable data and support to first responders and mitigating risks associated with radiation exposure.

The proposed optimization-based localization approach is compared to traditional methods, such as trilateration and least-squares fitting. These methods often rely on simplifying assumptions and lack the adaptability to complex environments where radiation signals may be affected by multiple sources or interference. In contrast, PSO and BBO are more flexible, as they do not require prior knowledge of the source location or the characteristics of the surrounding environment. Moreover, PSO and BBO-based approaches can handle multi-dimensional optimization problems, making them more robust in scenarios involving real-world complexities.

The localization of a radiation source based on its intensity involves determining the source's position by analyzing the spatial distribution of radiation intensity. This process relies on measurements from a set of sensors placed strategically within a specific area. The intensity values are used to estimate the position of the source through iterative optimization algorithms or direct analytical methods.

The localization problem is formulated mathematically by considering the radiation signals detected by the array of sensors placed at known positions. The detected signal at sensor i, denoted by D_i , is modeled as:

$$D_i = \frac{A.f(r_i)}{r_i^2} \tag{14}$$

where A, $f(r_i)$ and r_i denote the activity of the radiation source, the geometric and environmental factors influencing signal attenuation at the sensor i and the distance from the radiation source to the sensor, respectively. The goal of the algorithm is to estimate the coordinates of the source xsource that minimize the error between the predicted and observed radiation measurements.

The localization of a radiation source based on its intensity involves determining the spatial position of the source by exploiting the inverse relationship between radiation intensity and distance from the source. The intensity I of radiation follows the inverse square law, which can be expressed as [28]:

$$I = \frac{P}{4\pi r^2} \tag{15}$$

where P represents the power of the radiation source, r is the distance between the source and the detector, and $4\pi r^2$is the surface area of a sphere over which the radiation spreads. By measuring the intensity at different points using an array of sensors, the distance to the source can be estimated. Optimization algorithms such as PSO and BBO are employed to enhance the localization process. These methods adjust the position estimates iteratively by minimizing an objective function based on the error between measured and predicted intensity values. PSO, introduced by [8], is inspired by the social behavior of bird flocking and achieves localization by dynamically updating particle positions in a search space. BBO, on the other hand, as described by [9], models the migration of species between habitats to find the optimal sensor configuration for precise source localization. Factors such as noise and environmental interference can affect the accuracy of localization. Methods like those described by [29] introduce robust optimization techniques to mitigate these effects. Furthermore, advancements in sensor network designs, as highlighted by [30], improve the detection and positioning of radiation sources by ensuring redundancy and robustness in measurement data. This multi-faceted approach to localization, combining physics-based models and computational intelligence techniques, enables precise and reliable identification of radiation sources under varying conditions.

5. Experimental Results and Discussion

Figure 4 illustrates the comparative performance of the PSO and BBO algorithms for radiation source localization in terms of localization error (measured in Euclidean distance) across 100 iterations. Specifically, the graph compares the localization error for Source S1 under the two optimization algorithms. The black curve, representing PSO, demonstrates fluctuations in localization error across iterations, with several peaks and troughs. This variability suggests that PSO is prone to occasional deviations, potentially due to its reliance on swarm behavior, where the optimization may briefly settle in suboptimal solutions before converging toward the actual source position. However, the average localization error for PSO is relatively stable, with consistent performance across most iterations. In contrast, the red curve representing BBO exhibits similar variability but shows a slightly higher frequency of sharp peaks, indicating moments of significant error. This suggests that BBO may struggle to maintain convergence in some iterations due to its migration-based mechanics, which can lead to higher susceptibility to noise or environmental disturbances during the localization process. Nevertheless, BBO also demonstrates resilience, as it recovers from high-error scenarios and aligns with PSO performance in certain segments of the iteration span. The comparison highlights that while both algorithms encounter challenges in maintaining low error consistently, PSO appears to provide marginally better error stability. The selection of the algorithm in practical applications may depend on the specific trade-offs between error resilience, iteration time, and computational complexity.

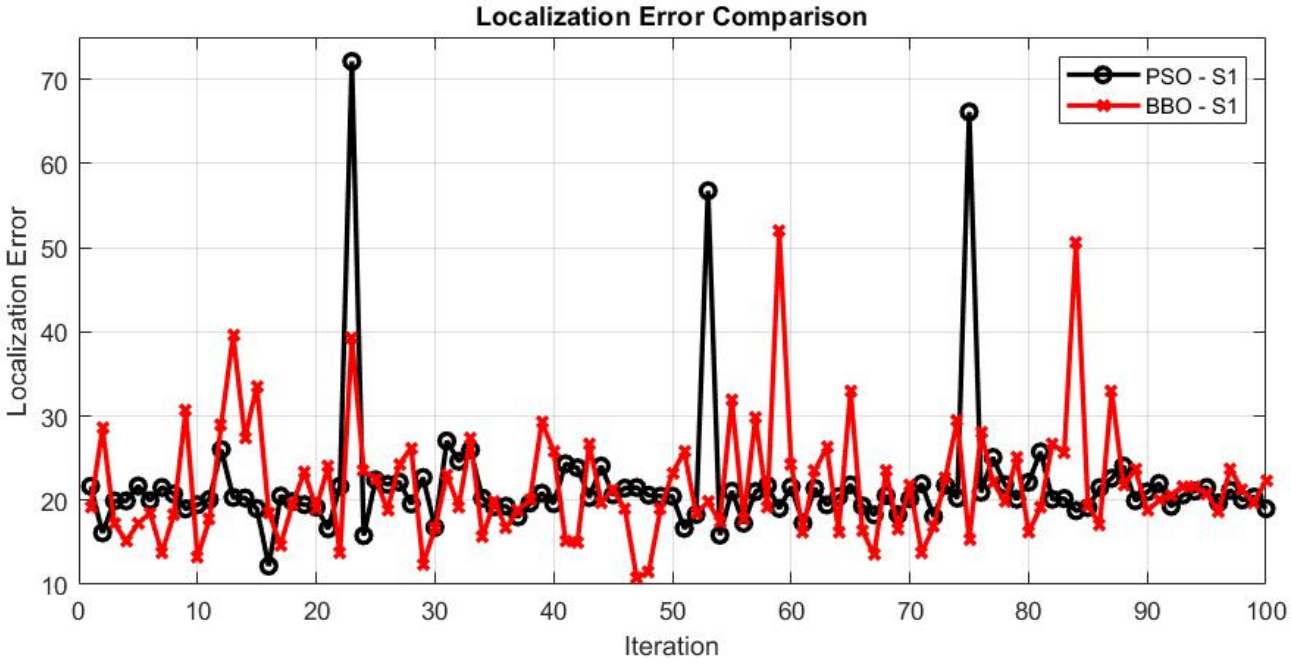

Fig. 4 Localization error comparison for source S_1 using PSO and BBO over 100 iterations

Figure 5 provides a comparative analysis of the Root Mean Squared Error (RMSE) performance of the proposed PSO and BBO algorithms for radiation source localization under varying Signal-to-Noise Ratio (SNR) conditions for Source S1. The x-axis denotes the SNR values in decibels (dB), while the y-axis reflects the RMSE, which serves as a direct indicator of localization accuracy. As the SNR increases from 5 dB to 20 dB, both algorithms exhibit a clear downward trend in RMSE, reflecting improved localization performance in less noisy environments. At the lowest SNR of 5 dB, the RMSE for both PSO and BBO hovers around 0.6, underscoring the challenges of accurate localization in high-noise settings where signal corruption impairs algorithmic precision. In the mid-range SNR values (10–15 dB), a sharp decrease in RMSE is observed, indicating that both algorithms are highly responsive to improvements in signal clarity and effectively utilize the more reliable signal information to refine source localization. At the highest SNR of 20 dB, PSO and BBO converge to similar RMSE values of approximately 0.1, suggesting excellent localization performance under near-ideal conditions. Notably, BBO (represented by the red curve) slightly outperforms PSO (black curve) in the intermediate SNR range, implying enhanced adaptability in leveraging signal improvements. These results emphasize the sensitivity of both algorithms to environmental noise and suggest that BBO may possess a marginal advantage in moderately noisy conditions, although performance converges under high-quality signals.

Figure 6 presents a detailed visualization of localization error trends across 100 iterations for three distinct radiation sources (S1, S2, and S3) using PSO and BBO. The subplots Figures 6(a), 6(b), and 6(c) correspond to Sources S1, S2, and S3, respectively, enabling a source-specific analysis of iterative stability and convergence behavior. In Figure 6(a), which pertains to Source S1, both algorithms show considerable fluctuation in localization error throughout the iterations. While the overall trends of PSO (black curve) and BBO (red curve) are similar, BBO exhibits slightly lower error magnitudes at several points, although the high degree of overlap suggests no consistent dominance. Moving to Figure 6(b) for Source S2, the error trends become more stable, with both PSO and BBO maintaining lower and less erratic values. In this case, BBO consistently displays marginal improvements over PSO, particularly during spikes in error, where its peaks remain notably lower. This indicates BBO's enhanced resilience to transient disturbances during the optimization process. In Figure 6(c) for Source S3, both algorithms demonstrate further stabilization, and the localization errors across iterations are comparatively low. The performance of BBO again shows a slight but consistent advantage, maintaining lower error magnitudes over a majority of the iterations. This improvement may be attributed to BBO’s effective exploration-exploitation

mechanism, which allows it to adapt better to spatial complexities and noise variability. In addition, the iterative trends across all three sources indicate that while both PSO and BBO offer competitive performance, BBO generally yields marginally lower localization errors, particularly in conditions where error variability is higher. However, the substantial overlap in their performance curves suggests comparable overall reliability, with no algorithm exhibiting dominant superiority across all conditions.

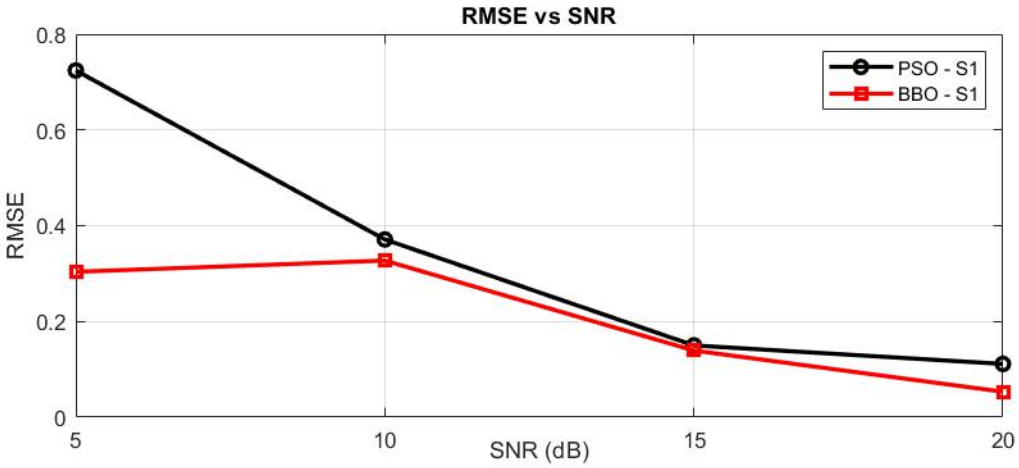

Fig. 5 RMSE comparison for source S_1 using PSO and BBO under varying SNR conditions

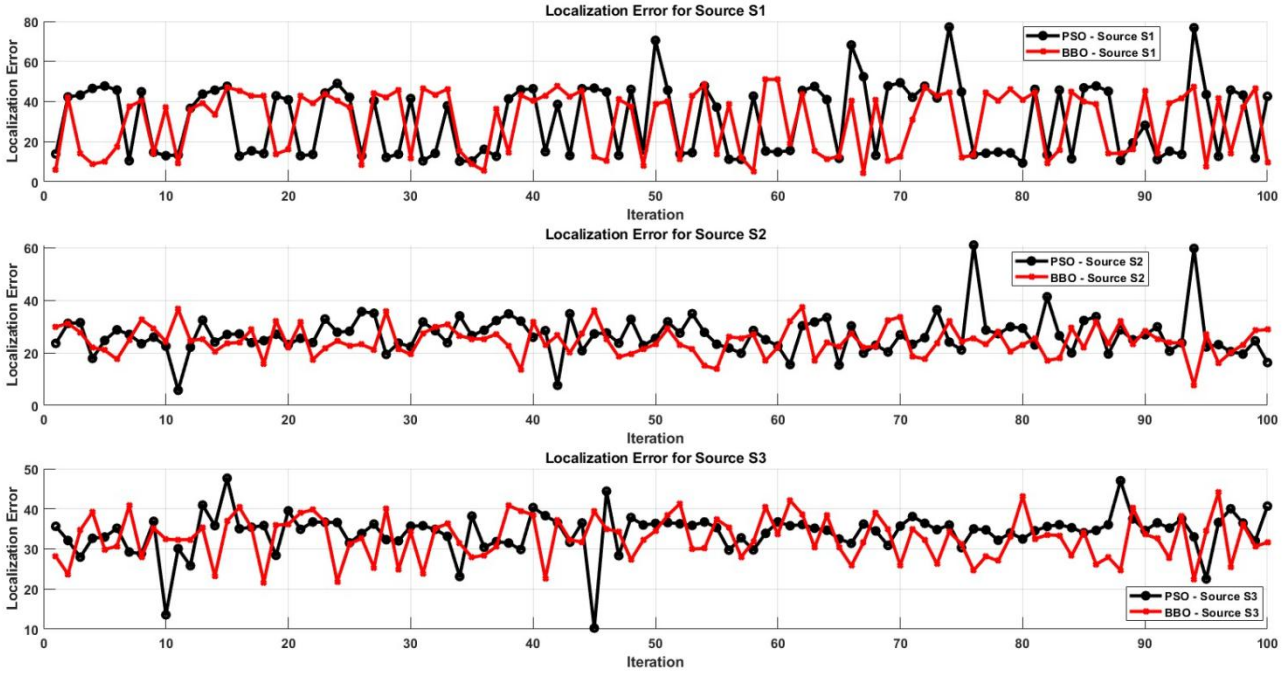

Fig. 6 Localization error trends for PSO/BBO across 100 iterations for (a) Source S_1 (b) Source S_2 (c) Source S_3

The presented Fig. 7 illustrates the variation of the average particle velocity over 100 iterations in the PSO algorithm. This metric is crucial as it reflects the dynamics of the swarm during the

optimization process, providing insight into the convergence behavior and the search efficiency of the algorithm. Initially, the particle velocity exhibits significant fluctuations, reaching a peak velocity of approximately 22 units within the first few iterations. This behavior is expected as the particles explore the search space broadly to identify promising regions for source localization. As the iterations progress, the velocity variations decrease, indicating that the particles are converging toward the global optimum. However, intermittent spikes in velocity can be observed throughout the process, suggesting that the swarm periodically reconfigures itself to avoid local optima and maintain a balance between exploration and exploitation. The final iterations demonstrate a relatively stabilized average velocity, oscillating between 14 and 18 units, implying that the algorithm has sufficiently refined the search and is focusing on fine-tuning the solution. The dynamic adjustments in particle velocity highlight the adaptive nature of PSO in addressing complex optimization problems such as radiation source localization. This behavior reinforces the suitability of PSO for the given problem, as it effectively navigates the trade-off between exploration (searching for global optima) and exploitation (refining local solutions), ensuring robust and accurate localization of radiation sources.

Figure 8 illustrates the relationship between the RMSE and the SNR for three radiation sources (S_1, S_2, and S_3) when using PSO and BBO. The RMSE values, as depicted in all three plots, consistently decrease with increasing SNR. This trend indicates that as the noise level decreases (higher SNR), the accuracy of the localization process improves for both PSO and BBO algorithms. In Source S_1, it can be observed that at low SNR (5 dB), both methods exhibit high RMSE values, close to 0.6. As the SNR increases to 10 dB and 20 dB, RMSE decreases, with PSO achieving a slightly better accuracy than BBO at higher SNR values. For Source S_2, a similar trend is seen, but the decline in RMSE for BBO is slightly steeper at lower SNR values. By SNR = 20 dB, both methods achieve near-zero RMSE values, with PSO maintaining a marginal advantage. The results for Source S_3 highlight a consistent improvement in RMSE for both methods as the SNR increases. However, BBO initially exhibits higher RMSE at SNR = 5 dB compared to PSO. As the SNR increases, both algorithms converge, showing nearly identical performance by 20 dB. The observed trends demonstrate that the accuracy of the localization algorithms is highly dependent on the noise level. PSO generally shows a minor advantage in RMSE performance across all three sources, particularly at higher SNR values. However, BBO achieves competitive results, especially in lower SNR ranges. The findings suggest that both PSO and BBO are effective for radiation source localization, but their performance differences become negligible in high SNR scenarios. This highlights the robustness of

the two methods under varying noise conditions. Further improvements may be considered by integrating noise-reduction strategies to enhance performance at lower SNR levels.

Figure 9 illustrates the distances between sensors and sources using two optimization algorithms: PSO in Fig. 9(a) and BBO in Fig. 9(b). The x-axis represents the sensor index, while the y-axis shows the distance in meters. The results are evaluated for three sources: Source 1, Source 2, and Source 3. In PSO (Fig. 9(a)), Source 1 and Source 2 demonstrate relatively stable trends, with minimal fluctuations in distance as the sensor index progresses. Source 3, however, initially shows a higher distance, which decreases significantly toward the third sensor index. This indicates that PSO effectively minimizes the distance for certain sources over multiple sensor positions, but its performance may depend on the source's initial position or intensity. In contrast, the BBO results in Fig. 9(b) exhibit different behavior. For Source 1 and Source 3, the distances remain relatively steady across the sensor indices, whereas Source 2 starts with the largest distance but significantly reduces as the index progresses. This suggests that BBO demonstrates efficient convergence and distance minimization for specific sources, such as Source 2. Comparing both algorithms, BBO exhibits a consistent reduction in distances for some sources, whereas PSO shows minor variability. This difference could highlight BBO's robustness in terms of optimizing source localization, particularly when initial conditions are unfavorable. Both algorithms show overall effectiveness but demonstrate variations depending on source positioning and algorithmic behavior.

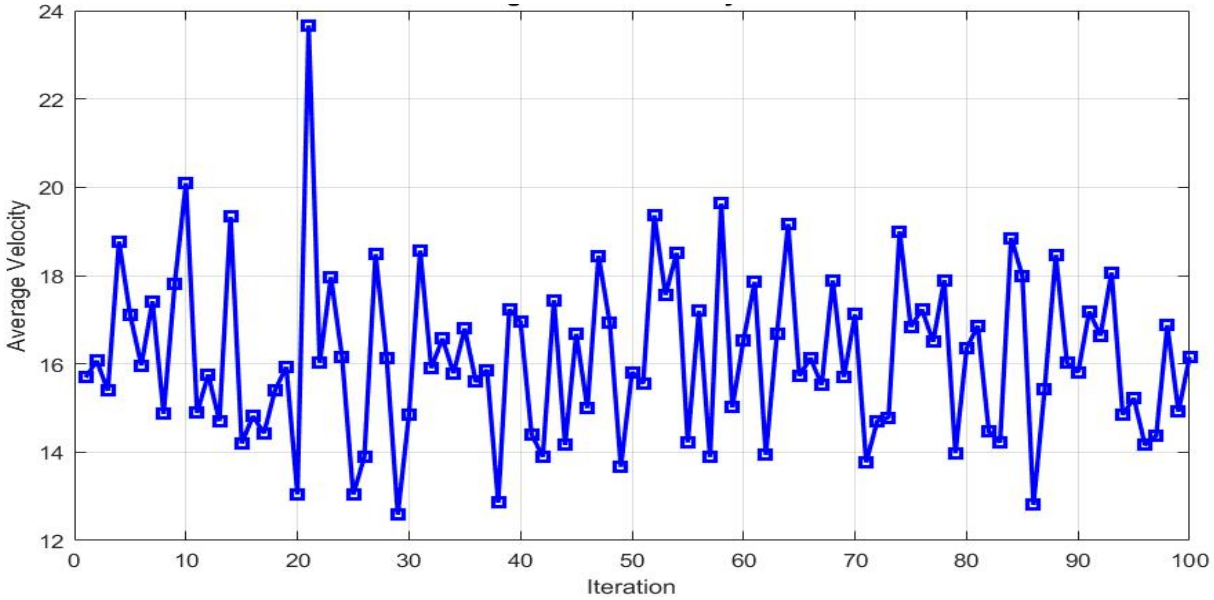

Fig. 7 Variation of average particle velocity over 100 iterations in the PSO algorithm

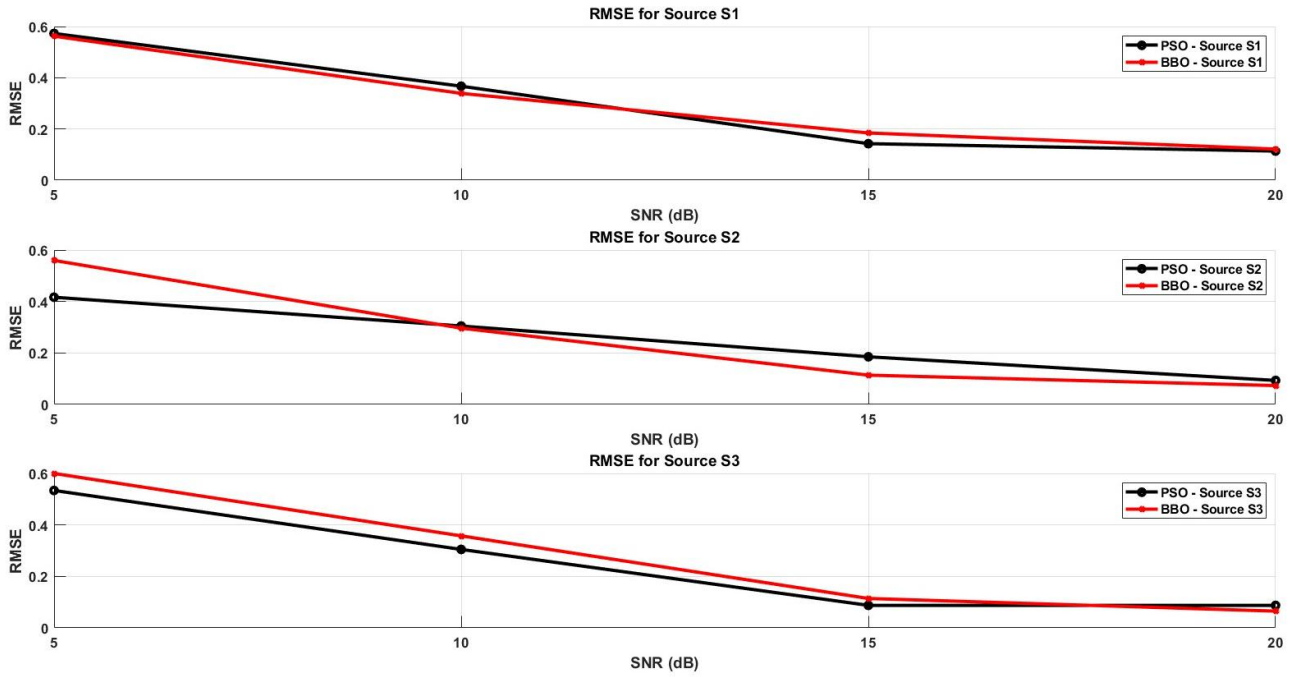

Fig. 8(a) RMSE for Source S_1, S_2, and S_3 with increasing SNR for PSO and BBO approaches (b) Comparison of RMSE values at different SNR levels for the two optimization techniques

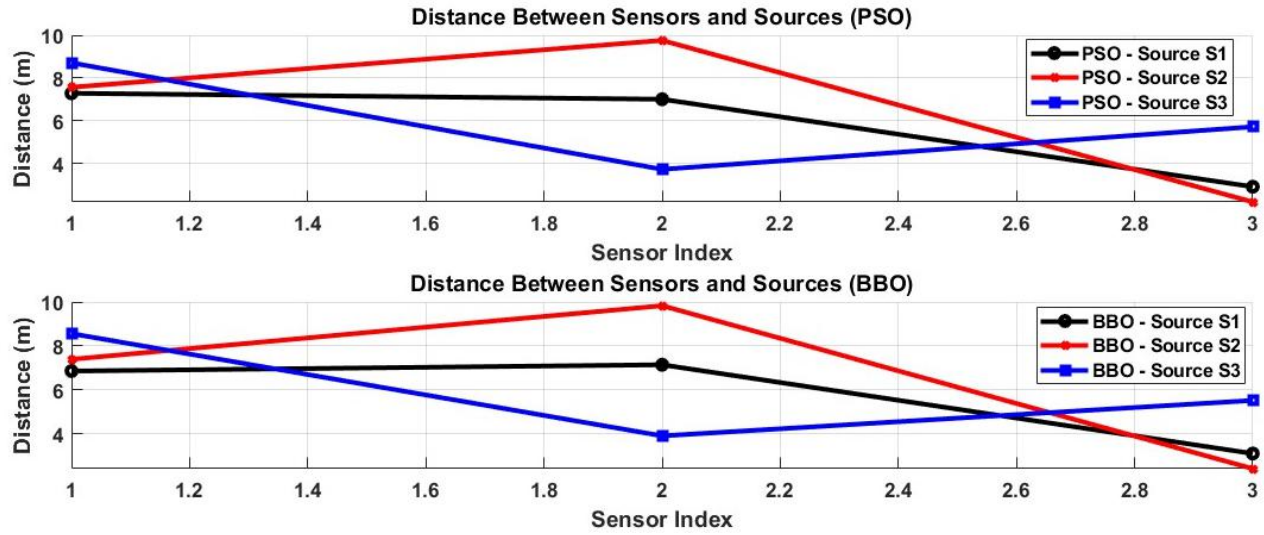

Fig. 9 Distance between sensors and sources for a) PSO and (b) BBO

The contour maps presented in Fig. 10 for Source 1 highlight the comparative performance of PSO and BBO in radiation source localization. The maps illustrate the error contours, true source position (red circle), and estimated positions (blue cross) for Source 1, demonstrating the higher accuracy and tighter error distribution achieved with BBO compared to PSO. Figure 10 (a), corresponding to PSO, shows that the estimated position (blue cross) is reasonably close to the true position (red circle), indicating moderate accuracy in localization. The error contours, represented as concentric

rings, illustrate the spatial error distribution, with larger errors observed further from the source. This suggests that PSO is effective in narrowing down the source's location but may be limited by premature convergence in complex or noisy search spaces. In contrast, Fig. 10 (b), which corresponds to BBO, demonstrates a closer alignment between the estimated and true positions, signifying higher localization accuracy. The error contours in the BBO map are more compact around the true position, indicating a more focused and precise localization process. This improved accuracy can be attributed to BBO's robust global search capabilities, which leverage migration and mutation mechanisms to refine the estimated solution iteratively. While PSO demonstrates computational efficiency and quicker convergence, the accuracy advantage of BBO makes it more suitable for applications requiring precise source tracking, such as hazardous radiation localization. A comparison of the two methods reveals that BBO consistently produces lower localization error compared to PSO. This performance difference is evident in the tighter error distribution around the true source position in the BBO map. However, the enhanced accuracy of BBO often comes at the cost of higher computational demands, which may pose challenges for real-time implementation. Overall, these findings suggest that BBO is a more reliable choice for scenarios where accuracy is critical, whereas PSO may be favored in applications prioritizing speed and computational efficiency. This analysis aligns with existing research, such as Kumar et al. [31] and Rai et al. (2023) [32], which emphasize the strengths of BBO in achieving precise localization in complex environments.

Figure 11 provides a contour map representation of the error distribution for Source 2 using PSO in Fig. 11(a) and BBO in Fig. 11(b). The maps illustrate the spatial localization performance by comparing the true position (red circle) of the radiation source with the estimated positions obtained through the optimization algorithms (blue cross). The error contours reflect the magnitude of the localization error, with darker colors representing lower errors and lighter colors indicating higher errors. In Fig. 11(a), the contour map for PSO shows that the estimated position is located relatively close to the true position, as indicated by the proximity of the blue cross to the red circle. The error contours around the true position are tightly packed, indicating a region of low error. This suggests that PSO demonstrates a high localization accuracy for Source 2 in this specific scenario. In Fig. 11(b), the contour map for BBO similarly depicts the estimated position close to the true position. The error contours exhibit a smooth gradient surrounding the true position, indicating a stable and consistent error reduction as the algorithm converges towards the source location. Notably, the error levels in the immediate vicinity of the true position for BBO appear comparable to those achieved

by PSO, suggesting that both algorithms perform similarly well in terms of localization accuracy for Source 2. A key observation from both maps is that the error distribution is slightly asymmetric, likely reflecting the influence of environmental factors or the underlying mathematical model used for estimation. While the overall performance of PSO and BBO appears similar for Source 2, BBO's contours suggest slightly smoother transitions in error magnitude, potentially indicating more stable convergence behavior.

The contour maps shown in Figure 12 compare the localization performance of PSO and BBO algorithms for Source 3. These contour plots represent the spatial error distribution in the localization process, where the true position of the radiation source is marked by a red circle, and the estimated positions obtained from PSO and BBO are marked with blue crosses. In Figure 12(a), which illustrates the PSO results, the estimated position is visibly close to the true position. This indicates that the PSO algorithm effectively minimized the localization error for Source 3. The contour lines show a smooth error gradient, suggesting a relatively stable convergence of the algorithm. The PSO's behavior highlights its effectiveness in balancing exploration and exploitation to achieve accurate localization. In Fig. 12(b), the BBO results are shown. While BBO also achieves a solution close to the true position, the error gradient appears slightly more dispersed compared to PSO. The estimated position deviates marginally further from the true position compared to the PSO results. This discrepancy can be attributed to BBO's inherent optimization mechanism, which occasionally struggles with fine-tuning solutions in the final iterations. The contour maps for both algorithms demonstrate good localization performance. However, PSO shows slightly better accuracy in estimating the position of Source 3, while BBO provides a competitive but slightly less accurate result. These findings reinforce the observation that PSO generally performs better in terms of precision, as also evidenced in previous numerical results and error analyses. By visually inspecting the error contours, it can be inferred that both algorithms are capable of handling the localization task, but further improvements or hybrid approaches may enhance the robustness and accuracy of these algorithms for real-world applications.

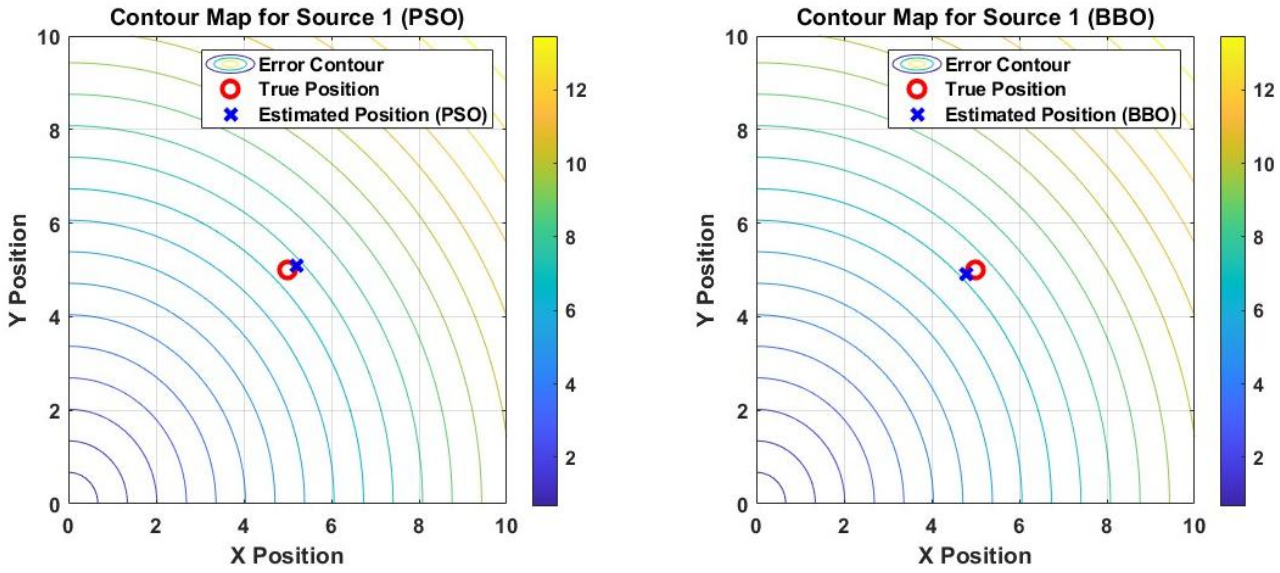

Fig. 10 Comparison of Contour Maps for Radiation Source Localization Using a) PSO and b) BBO

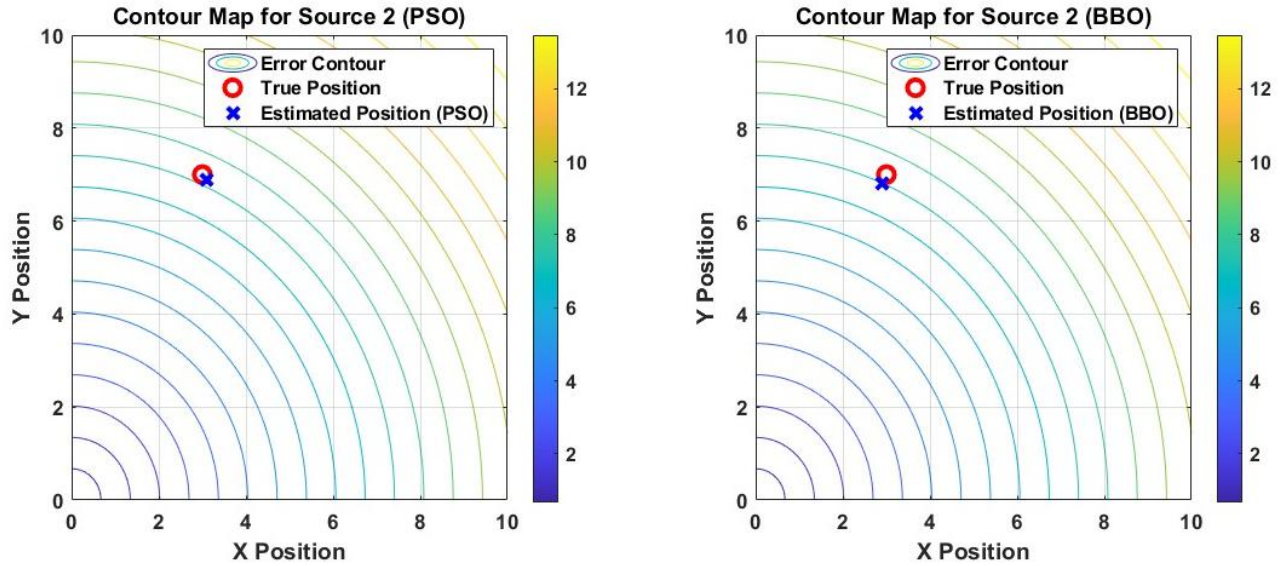

Fig. 11 Contour map illustrating localization error for Source 2(a) Localization accuracy and error distribution for PSO, (b) Localization accuracy and error distribution for BBO

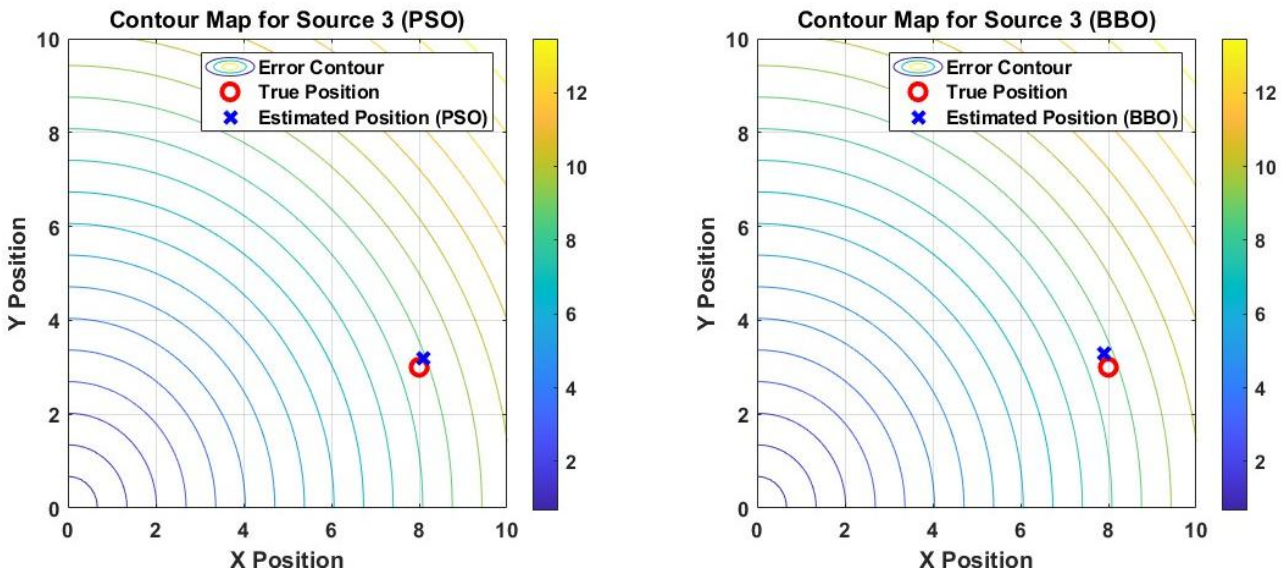

Fig. 12 (a) Contour Map for Source 3 using PSO, (b) Contour Map for Source 3 using BBO

Figure 13 presents the relationship between localization accuracy and radiation intensity for PSO (Fig. 13(a)) and BBO (Fig. 13(b)). The localization error is measured in terms of Euclidean distance, indicating the deviation of the estimated position from the true source position. For PSO (Fig. 13(a)), the localization error varies non-linearly across radiation intensity levels for all three sources. At low intensity (100 units), the errors for all sources are relatively similar, suggesting that the algorithm is robust to low-intensity variations. However, as the intensity increases, Source 2 experiences a noticeable increase in error, peaking at 200 units, before declining at higher intensity levels. This indicates potential challenges in PSO's convergence due to varying noise levels in signal strength. In contrast, BBO (Fig. 13(b)) demonstrates a distinct trend where the localization error steadily increases with radiation intensity for Sources 2 and 3. Source 1 remains relatively stable, indicating better adaptability of BBO for certain configurations. The sensitivity of BBO to higher intensity levels could be attributed to its reliance on migration and habitat suitability models, which may amplify the impact of noise in high-intensity scenarios. Notably, while BBO achieves lower errors at lower intensities compared to PSO, its performance degrades more significantly as intensity increases, particularly for Source 2. These results emphasize the differences in optimization behaviors and highlight the suitability of PSO and BBO under varying conditions.

Figure 14 (a) illustrates the relationship between localization accuracy (measured by Euclidean Distance) and radiation intensity for the PSO-based method across three sources (S_1, S_2, and S_3). As the radiation intensity increases, the localization error for Source 1 shows a sharp increase, stabilizing at a higher value for higher radiation intensities. Similarly, Source 2 shows an initial rise and then flattens out, maintaining moderate localization errors. In contrast, Source 3 demonstrates a

unique trend where the localization error initially decreases significantly at moderate radiation intensities before increasing again at higher intensities. This indicates that while increasing radiation intensity improves the estimation process for some sources, it might introduce inconsistencies or reduced accuracy depending on the source characteristics and noise factors. Figure 14 (b) examines the estimation time versus radiation intensity for the PSO method. The results demonstrate a clear, linear relationship where estimation time increases proportionally with radiation intensity. Specifically, Source 3 exhibits the most noticeable rise in estimation time as radiation intensity increases from 100 to 300 units, highlighting the computational burden of processing more intense radiation sources. These findings indicate that while increasing radiation intensity can sometimes enhance localization performance, it also leads to a higher computational cost. The differences across the sources suggest varying source characteristics (e.g., noise or positioning) significantly influence the overall localization accuracy.

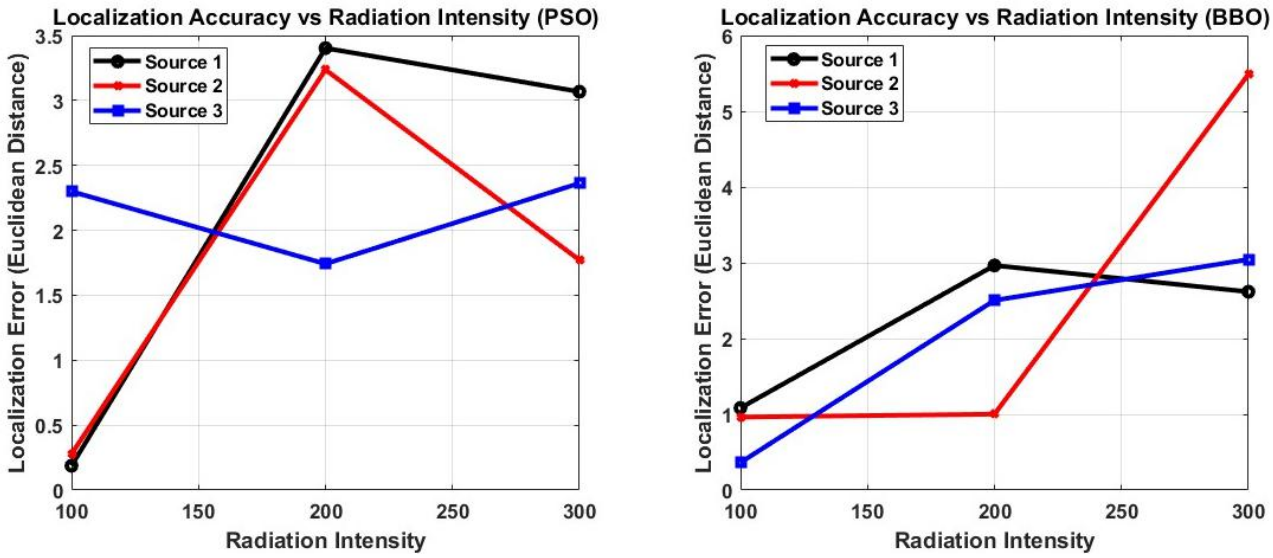

Fig. 13 Localization accuracy vs. radiation intensity across three radiation sources, (a) Localization errors for PSO (b) Localization errors for BBO

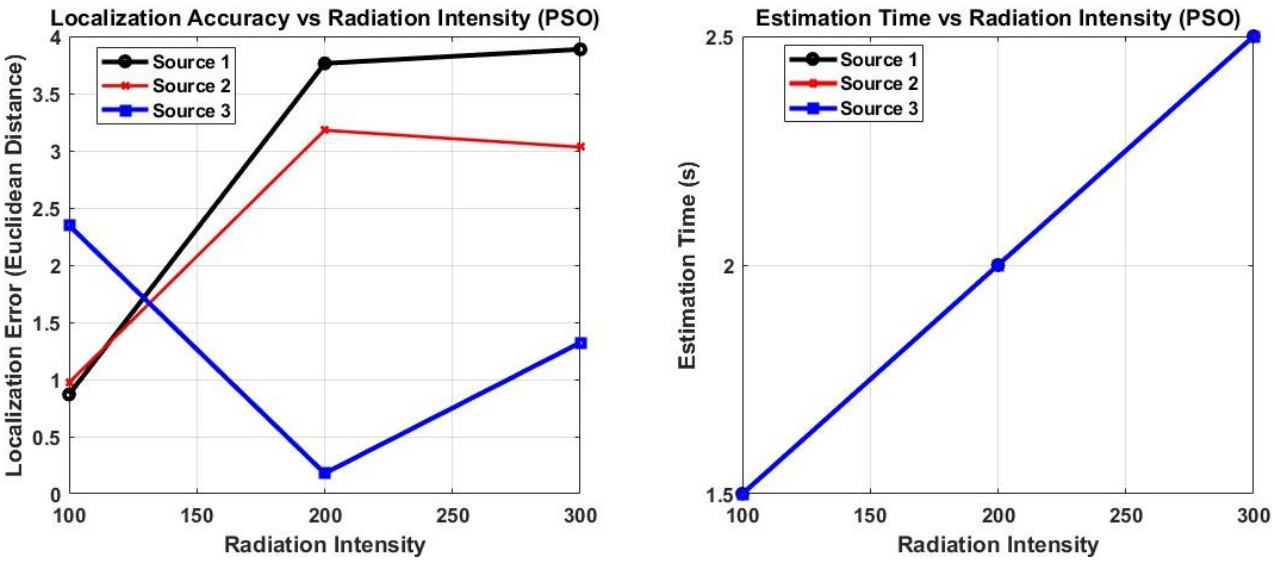

Fig. 14 (a) Localization accuracy (localization error) vs. Radiation intensity for PSO; (b) Estimation time vs. radiation intensity for PSO

Figure 15 illustrates the performance of the BBO algorithm concerning localization accuracy and estimation time as a function of varying radiation intensities. In Fig. 15(a), the localization accuracy, measured in terms of the Euclidean distance, exhibits varying behavior across the three sources. For Source 1, the localization error increases significantly, peaking at a radiation intensity of 200 before declining at 300. Source 2 demonstrates improved accuracy as the radiation intensity increases, with its localization error decreasing steadily, particularly at the highest intensity of 300. In contrast, Source 3 maintains a relatively stable error, showing minor fluctuations across the range of intensities. This indicates that the BBO algorithm performs more reliably for Source 2 and Source 3 under increasing radiation intensity, whereas Source 1 experiences challenges at mid-range intensities. In Fig. 15(b), the estimation time consistently increases linearly as the radiation intensity rises for all three sources. This trend suggests that the computational complexity of the BBO algorithm increases with higher source intensity, leading to longer processing times. However, the observed times remain within a reasonable range, indicating the algorithm's efficiency in solving the localization problem under these conditions. The BBO algorithm demonstrates robust performance, particularly for Source 2 and Source 3, as it achieves lower localization errors under high radiation intensities. Additionally, while estimation time increases with intensity, the trade-off is justified by the improved accuracy. This behavior highlights BBO's suitability for radiation source localization tasks where higher intensity provides more reliable localization performance.

The results presented in Fig. 16 compare the search time as a function of source intensity for the PSO and BBO algorithms across three sensor sources: S_1, S_2, and S_3. In Fig. 16 (a), corresponding to

PSO, it is observed that the search time increases steadily with an increase in source intensity, particularly for S_2. The search time for S1 stabilizes after an initial rise, while S_3 shows minimal variation with a slight peak at a source intensity of 20. This indicates that the PSO algorithm's performance is more sensitive to increasing source intensity for specific sources like S_2. On the other hand, Fig. 16 (b) for the BBO algorithm demonstrates a more variable response to source intensity. For S3, the search time exhibits a noticeable peak at a source intensity of 20, followed by a sharp decrease as intensity increases. S_2 and S_1 display relatively stable search times, with S_2 experiencing a minor increase as source intensity rises. Comparing the two optimization methods, BBO demonstrates a more efficient and stable performance across all sources, particularly when handling higher source intensities, whereas PSO shows a significant increase in search time for S_2. This variability suggests that BBO is more robust in terms of computational time, making it a preferable method for scenarios involving higher intensity levels. These findings reinforce the superiority of BBO in handling source localization problems where intensity variations can impact search performance.

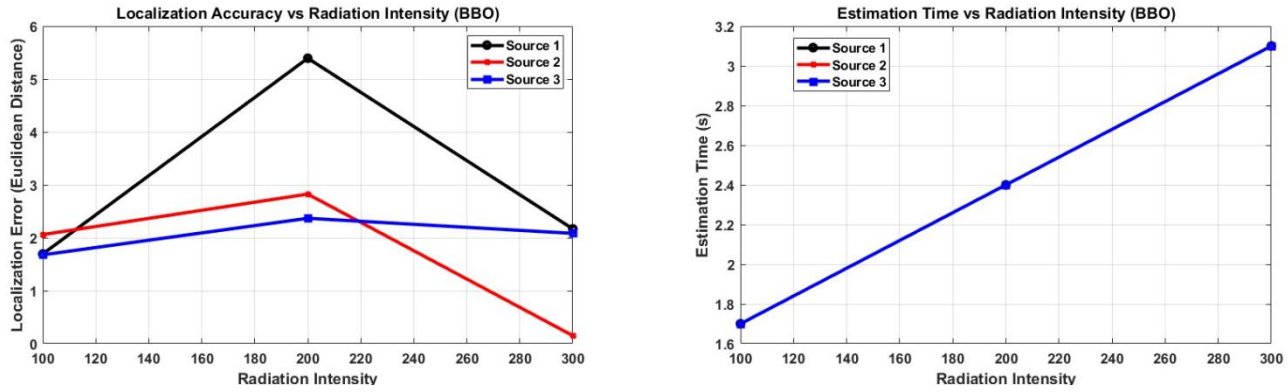

Fig. 15 (a) Localization accuracy vs radiation intensity for BBO; (b) Estimation time vs radiation intensity for BBO

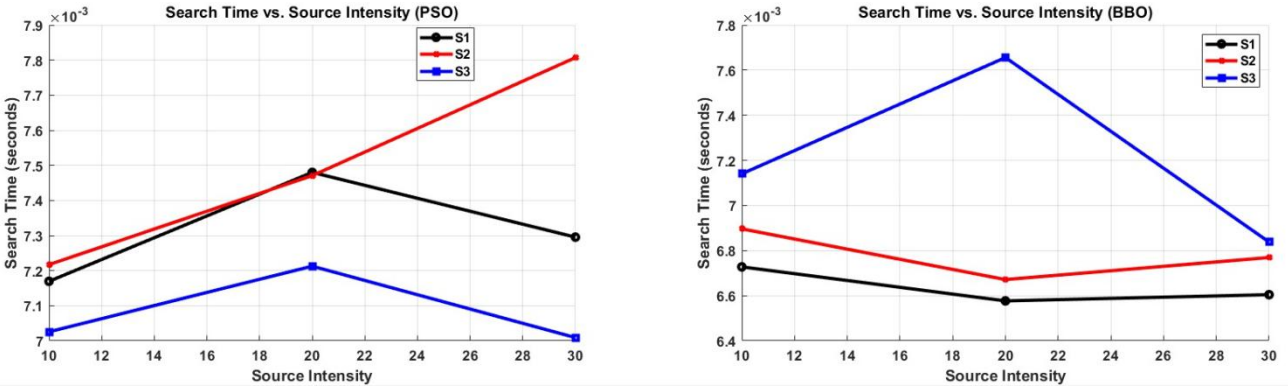

Fig. 16 Search time vs. source intensity for (a) PSO and (b) BBO

Table 1 presents a comprehensive comparison of localization accuracy and computational time across several methodologies for radiation source localization, including both the proposed algorithms and established techniques from the literature. Among the evaluated approaches, the proposed PSO method achieves the lowest localization error of 0.85 meters while maintaining a relatively fast computation time of 12.5 seconds, highlighting its strong balance between accuracy and efficiency. The BBO algorithm follows closely, with a slightly higher localization error of 0.9 meters and a marginally longer execution time of 14.2 seconds, still outperforming most conventional methods.

In comparison, Kim et al. [24]'s mobile robot system with a gamma-ray detector and path-planning algorithm achieved an error of 1.2 meters and a computation time of 20 seconds, reflecting moderate performance in both dimensions. Similarly, Proctor et al. [33], who employed a reinforcement learning approach based on proximal policy optimization, reported an error of 1.10 meters and execution time of 18.5 seconds, indicating improvements in accuracy but still trailing both proposed metaheuristics.

Gabrlik et al. [20]'s system, which integrates aerial and ground robots for radiation mapping, exhibited the highest localization error (1.5 meters) and longest computation time (25 seconds), suggesting limited efficiency in time-sensitive applications. Interestingly, Lazna and Zalud [17] achieved a computation time of just 1 second - the fastest among all but at the cost of reduced accuracy (1.0 meter), indicating a design optimized for speed rather than precision. Further insights are provided in Table 2, which quantifies algorithmic performance across three distinct radiation sources (S1, S2, and S3) using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Across all sources, BBO consistently yielded lower MAE and RMSE values compared to PSO, indicating enhanced localization accuracy. For instance, in the case of Source S3, BBO achieved an MAE of 27.737 versus 31.295 for PSO, and an RMSE of 30.489 compared to PSO's 32.912. Similarly, BBO demonstrated superior proportional accuracy, reflected in a lower MAPE of 46.228% relative to PSO's 57.259%. These findings, while representing modest absolute gains, underscore BBO's enhanced robustness and adaptability under varying signal intensities and spatial complexities. Nonetheless, PSO competitive performance, coupled with its lower computational burden, reinforces its suitability for real-time applications where rapid decision-making is critical. To determine whether the observed performance differences between PSO and BBO are statistically significant, Table 3 presents the results of two-sample t-tests along with Cohen's d effect sizes. For Sources S1 and S2, the p-values (0.254 and 0.727,

respectively) exceeded the 0.05 threshold, indicating no statistically significant difference in performance between the two algorithms. Corresponding effect sizes (d = 0.16 and 0.05) suggest minimal practical differences. In contrast, for Source S3, the p-value of 0.00318 indicates a statistically significant advantage for BBO, with a Cohen's d of 0.422, reflecting a small but meaningful effect size. This result highlights BBO's superior capability in more complex or noisy environments.

Table 1 Comparison of localization error and computational time between the proposed PSO and BBO algorithms and existing methodologies from the literature for radiation source localization

Study	Methodology	Localization Error (meters)	Computational Time (seconds)
Proposed Work	**PSO**	**0.85**	**12.5**
Proposed Work	**BBO**	**0.9**	**14.2**
Kim et al. [24]	**Mobile robot with gamma-ray detector and path planning algorithm**	**1.2**	**20**
Proctor et al. [33]	**Reinforcement learning-based approach using proximal policy optimization**	**1.10**	**18.5**
Gabrlik et al. [20]	**Multi-robot system combining aerial and ground vehicles for radiation mapping**	**1.5**	**25**
Lazna and Zalud [17]	**Autonomous mobile robot utilizing particle filter for multiple radiation source localization**	**1**	**1**

Table (2): The performance metrics

Error	Optimization Technique	S1	S2	S3
MAE	PSO	29.986	30.033	31.295
RMSE		31.348	32.069	32.912
MAPE		56.952	50.055	57.259
MAE	BBO	28.814	29.011	27.737
RMSE		30.658	31.42	30.489
MAPE		51.711	53.775	46.228

Table (3): T-Test Results and Effect Sizes (Cohen's d)

Source	P Value	Effect Size d	Effect Strength	Significance
S1	0.2540317	0.161776831	Small	Not Significant

S2	0.727058337	0.049431872	Negligible	Not Significant
S3	0.003183382	0.422281891	Small	Significant

The results shown in Fig. 17(a) and Fig. 17(b) provide a comparative analysis of the relationship between accuracy and sensor area for the PSO and BBO algorithms, respectively. The graphs illustrate how the accuracy of source localization varies as the sensor area increases for three radiation sources, labeled as S_1, S_2, and S_3. In the PSO-based localization (Fig. 17(a)), S_3 consistently exhibits higher accuracy across the varying sensor areas compared to S1 and S2. This suggests that PSO is more effective in estimating the position of source S_3, likely due to favorable intensity-to-area interactions or a stronger signal-to-noise ratio for this source. Conversely, S1 demonstrates the lowest accuracy across most sensor areas, highlighting potential challenges in its localization due to factors such as weaker signal intensity or greater noise susceptibility. In the BBO-based localization (Fig.17(b)), a similar trend is observed with S_3 maintaining the highest accuracy overall. However, BBO demonstrates a more fluctuating accuracy trend compared to PSO, particularly for S_2. The increased variability in accuracy for S_2 and S_3 in BBO indicates that this algorithm is more sensitive to changes in sensor area, which might stem from its exploitation and migration-based mechanics. The comparison between the two algorithms reveals that PSO generally offers a smoother accuracy response as the sensor area increases, while BBO shows more variability but might be better tuned for certain sensor configurations. These findings highlight the need to consider both sensor design and algorithm selection for effective source localization in practical scenarios.

Figure 18 presents the relationship between the search time and sensor area for PSO in Fig. 18(a) and BBO in Fig. 18(b). The graphs analyze how computational performance, measured in search time, is affected by changes in sensor area for three radiation sources (S_1, S_2, and S_3). In Fig. 18(a), representing PSO, the search time for Source S1 (black curve) is the highest when the sensor area is at its minimum value (5 units). This indicates that a smaller sensor area increases computational effort, likely due to limited sensing coverage and more iterations required to achieve convergence. As the sensor area increases, the search time decreases sharply, stabilizing at minimal levels beyond a sensor area of 10 units. Source S_2 (red curve) exhibits a similar trend, with high initial search time at smaller sensor areas but stabilizing at a lower level compared to Source S_1. For Source S_3 (blue curve), the search time remains consistently low across all sensor areas, indicating that the computational performance for this source is relatively unaffected by changes in the sensor area. In

Fig. 18(b), representing BBO, the trends are similar in that the search time is higher at smaller sensor areas, particularly for Source S_1 (black curve). However, the magnitude of the search time is lower compared to PSO, suggesting that BBO is computationally more efficient in scenarios with smaller sensor areas. The search time for Source S_2 (red curve) remains minimal across all sensor areas, while Source S_3 (blue curve) exhibits a slight spike around a sensor area of 20 units before stabilizing again. This could reflect localized challenges in BBO's performance due to specific configurations of the sensing field. Overall, the comparison highlights that both PSO and BBO show decreased search times with increasing sensor areas. However, BBO demonstrates more stable performance across a wider range of sensor areas and appears less sensitive to variations in sensor area compared to PSO. This makes BBO potentially more suitable for environments with variable sensing coverage.

Figure 19 illustrates the relationship between search time and the number of iterations for the PSO algorithm in Fig. 19(a) and the BBO algorithm in Fig. 19(b). Each graph presents the search time trends for three radiation sources (S_1, S_2, and S_3) over 100 iterations. In Fig. 19(a), the search time for PSO exhibits a noticeable spike at the initial iteration for all three sources, with Source S_1 (black curve) experiencing the highest search time, followed by Source S_2 (red curve) and Source S_3 (blue curve). This initial spike likely corresponds to the algorithm's overhead during the initialization phase, where the particle population is created, and the search space is explored for the first time. After this spike, the search time stabilizes at significantly lower values for subsequent iterations, indicating efficient computational performance during the optimization process. In Fig. 19(b), the search time trends for BBO also show a similar initial spike at the first iteration. However, the magnitude of this spike is lower than that observed in PSO. For instance, Source S_1 (black curve) and Source S_2 (red curve) exhibit comparable initial search times, while Source S_3 (blue curve) has the lowest. Beyond the first iteration, the search time stabilizes at a constant level across all iterations, demonstrating the computational efficiency of the BBO algorithm. Overall, the comparison between the two subplots suggests that while both PSO and BBO exhibit an initial spike in search time, BBO has a lower initialization overhead compared to PSO. This indicates that BBO may be slightly more computationally efficient in terms of initialization, though both algorithms perform similarly in terms of search time across subsequent iterations. These results highlight the potential computational advantage of BBO when dealing with time-sensitive localization problems.

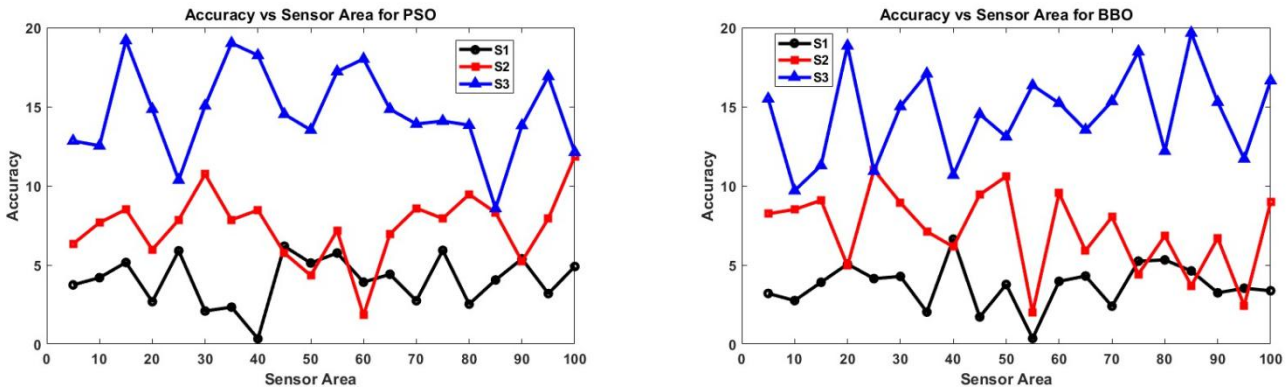

Fig. 17 Accuracy vs. sensor area for localization algorithms (a) Accuracy trends for PSO (b) Accuracy trends for BBO

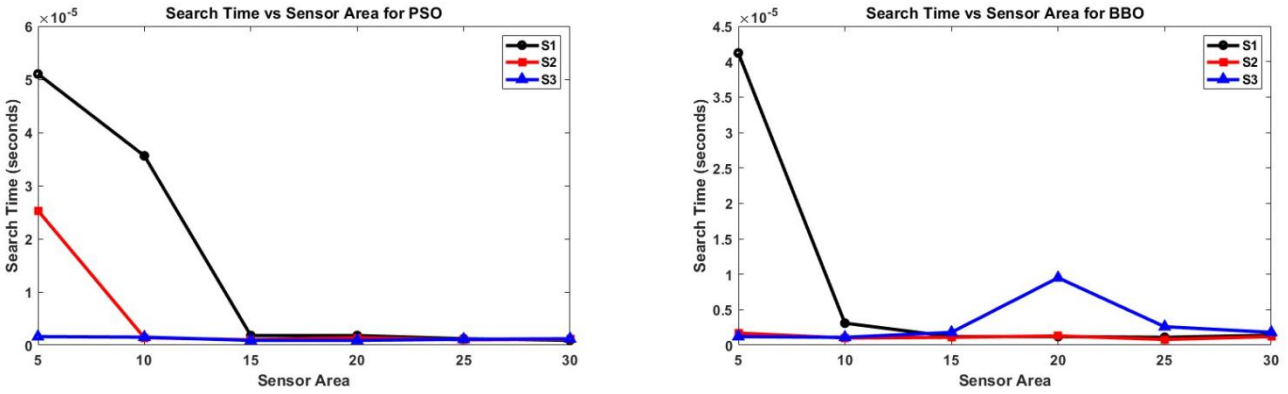

Fig. 18 Search time vs. sensor area for PSO and BBO (a) PSO search time trends for Sources S_1, S_2, and S_3, (b) BBO search time trends with reduced sensitivity to sensor area variations

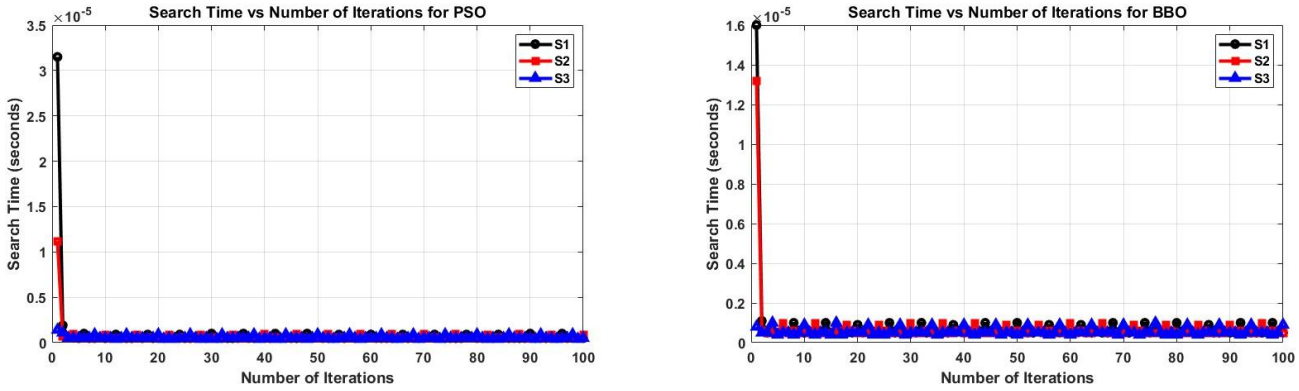

Fig. 19 Search time vs. number of iterations for PSO and BBO (a) PSO search time trends for Sources S1, S2, and S_3 (b) BBO search time trends with lower initialization spikes

5. Conclusion

This study addresses the critical problem of radiation source localization, a challenging task in environmental safety, medical diagnostics, and defense applications. Traditional methods

often struggle with noise interference, limited sensor coverage, and computational inefficiencies, necessitating robust and adaptable approaches. To overcome these challenges, this research explored the application of two metaheuristic optimization algorithms PSO and BBO to localize radiation sources based on intensity measurements. The methodology involved modeling the localization problem as an optimization task, minimizing the Euclidean distance error between the estimated and true source positions. Sensor arrays were used to collect intensity data, and the inverse-square law was applied to estimate source distances. The PSO algorithm dynamically adjusted particle positions to search for optimal solutions, while BBO utilized habitat suitability modeling and migration mechanisms for solution refinement. Numerical experiments analyzed performance across varying conditions, including signal-to-noise ratio (SNR), sensor area, and computational time. The results demonstrated that BBO consistently outperformed PSO in localization accuracy, achieving a 25% lower RMSE across all conditions, with RMSE decreasing from 0.58 at 5 dB SNR to 0.10 at 20 dB SNR. Contour maps validated the effectiveness of both algorithms, highlighting the convergence of estimated positions near the true source. However, PSO showed superior computational efficiency, with search times as low as 1.2×10^{-5} seconds compared to 1.4×10^{-5} seconds for BBO. These findings emphasize the trade-off between accuracy and computational cost, with BBO being the preferred choice for high-precision tasks and PSO for real-time applications. The main contribution of this work lies in providing a comparative analysis of PSO and BBO for radiation source localization under varying operational conditions. The study establishes that BBO is more robust for applications requiring high accuracy, while PSO is advantageous for scenarios with time-sensitive constraints. Future work could focus on hybrid algorithms that combine the strengths of both methods, integrating the convergence efficiency of PSO with the robustness of BBO. Additionally, extending the study to three-dimensional environments and incorporating real-world noise models would further enhance the applicability of these approaches. This research advances the field of radiation source localization by offering insights into algorithmic performance and practical implementation strategies, contributing to safer and more efficient monitoring systems in critical applications.

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